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Social vulnerability projections improve sea-level rise risk assessments

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ABSTRACT

Rising seas will impact millions of coastal residents in coming decades. The vulnerability of coastal populations exposed to inundation will be greater for some sub-populations due to differences in their socio-demographic characteristics. Many climate risk and vulnerability assessments, however, model current populations against future environments. We advance sea-level rise risk assessments by dynamically modeling environmental change *and* socio-demographic change. We project three scenarios of inundation exposure due to future sea-level rise in coastal Georgia from 2010 to 2050. We align the sea-level rise projections with five population projection scenarios of socially vulnerable sub-populations via the Hamilton-Perry method and the theory of demographic metabolism. Our combined fast sea-level rise and middle population scenarios project a near doubling of the population exposed, and a more than five-fold increase for those at risk (i.e., residing in a census tract with high social vulnerability) and most at risk (i.e., high social vulnerability and high exposure) compared to the same estimate based on 2010 population data. Of vulnerable sub-populations, women had the largest absolute increase in exposure for all scenario combinations. The Hispanic/Latinx population's exposure increased the largest proportionally under the fast and medium sea-level rise projections and elderly people's (65+) under the slow sea-level rise scenario. Our findings suggest that for coastal areas experiencing rapid growth (or declines) in more socially vulnerable sub-populations, estimates based on current population data are likely to underestimate (or overestimate) the proportion of such groups' risk to inundation from future sea-level rise.

1. Introduction

Global mean sea level is forecast to rise by as much as 2 m or more this century (DeConto & Pollard, 2016; Kopp et al., 2017, 2014; Sweet et al., 2017; Vermeer & Rahmstorf, 2009). By 2060, as much as 12% of the global population—1.4 billion people—could live in the low elevation coastal zone, many with the sustainability of their livelihoods linked to coastal environments (Neumann, Vafeidis, Zimmermann, & Nicholls, 2015). Under equal exposure to climate change hazards, however, the vulnerability of some coastal sub-populations will be much greater due to differences in their socio-economic characteristics (Gaillard et al., 2014; Jurgilevich, Räsänen, Groundstroem, & Juhola, 2017; Lutz and Muttarak 2017; Otto et al., 2017; Shepherd and KC 2015). Numerous case studies support the connections between increased vulnerability to environmental hazards and multiple socio-economic characteristics including non-white racial and non-Hispanic ethnic groups, women, people with low educational attainment or living in poverty, and both the young and elderly, as well as many other socio-economic factors (Bullard 1990; Bolin, Jackson, and Crist 1998; Ngo, 2001; Wisner, Blaikie, Cannon, & Davis, 2004; Bolin, 2007; Neumayer and Plümper 2007; Wailoo, 2010; Rufat, Tate, Burton, & Maroof, 2015; Shepherd and KC 2015). This suggests that assessing the risk of the most vulnerable coastal populations to inundation exposure from sea-level rise is increasingly important for improving coastal adaptation planning and policies. In this article, we define risk as a function of vulnerability, exposure, and hazard (see Jurgilevich et al., 2017).

Many climate risk and vulnerability assessments, however, model current populations against future environments (e.g., Emrich & Cutter, 2011; Frazier, Wood, Yarnal, & Bauer, 2010; Kopp et al., 2017; Kulp and Strauss 2017; Martinich, Neumann, Ludwig, & Jantarasami, 2013; Shepherd and Binita 2015; Spanger-Siegfried et al., 2017). This approach renders methods for assessing future climate risk as both static (population) and dynamic (environmental change). Only recently have studies of sea-level rise impacts started accounting for population change simultaneously with the associated environmental change expected from inundation (Neumann et al., 2015; Hauer, Evans, and Mishra 2016; Hauer 2017). These studies are limited to exposure assessments, however, quantifying the total future population expected to be impacted by sea-level rise inundation. They do not account for *who* that coastal population will be, in other words, its socio-demographic characteristics. Previous studies have compared future inundation

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exposure against either 1) current socially vulnerable populations, or 2) undifferentiated totals of future populations. Few, if any, have compared future inundation exposure against future projections of socially vulnerable sub-populations. Many of the previous studies have shown that a substantial portion of current coastal populations in the United States have sub-populations with increased levels of social vulnerability. Given this and the well-documented historical growth in US coastal populations (Crossett et al., 2013; Culliton et al., 2010) and its projected future growth (Hauer et al., 2016), such a temporal misalignment of comparing current social vulnerability against future inundation exposure will likely lead to incorrect estimates of the future risk of coastal populations.

The temporal misalignment in previous studies is due to limited methodological approaches for analyzing gradual environmental change in concert with multi-decadal socio-demographic change (Jurgilevich et al., 2017). Recent theoretical developments in demography, however, offer an approach for overcoming this shortcoming through a multi-dimensional predictive model of socio-demographic change called *demographic metabolism* (Lutz, 2013; Lutz and Muttarak 2017). Specifically designed for climate change research, demographic metabolism is a theoretical framework that argues that "the process of social change can be analytically captured through the process of younger cohorts replacing older ones" (Lutz, 2013, p. 284). The cohort aged 15–19 in 2015 becomes the 20–24 cohort in 2020 after adjusting for the components of population change: births, deaths, and migration. This approach creates reliable socio-demographic forecasts over decadal time scales for two key reasons: 1) many socio-demographic characteristics are either established at a young age (e.g., the proportion of people with a high school education aged 25–29 in 2015 is a good predictor of those aged 60–64 with a high school education in 2050) (Lutz and KC 2011), and 2) socio-demographic change is embedded within the age structure (e.g., life course analysis shows that earnings steadily increase after age 18, peaking around age 65, before declining through retirement) (Tamborini, Kim, and Sakamoto 2015).

In this article, we advance sea-level rise risk assessments by dynamically modeling environmental change *and* socio-demographic change of coastal populations. Specifically, we forecast inundation exposure due to future sea-level rise along with projections of the socio-demographic indicators of social vulnerability for populations in coastal Georgia. Given the high projections of US coastal population growth (Hauer et al., 2016), we examine the potential underestimation of previous estimates of social vulnerability to sea-level rise. We assess the total and proportional change in vulnerable sub-populations at risk to inundation by comparing estimates based on 2010 and 2050 population data. Our analysis allows us to capture the dynamic spatio-temporal relationship between shifts in socio-demographic indicators driving social vulnerability and increasing levels of inundation exposure from future sea-level rise.

2. Methods

2.1. Study area

We selected coastal Georgia in the United States as our study area given its rural-to-urban settings and diverse demographics including relatively high numbers of people with the characteristics that are indicated to increase social vulnerability (Fig. 1) (Cutter, Boruff, and Shirley 2003; Wisner et al., 2004). Of the greater than 500,000 people residing in the six coastal county region, roughly 227,000 (44%) are racial and/or ethnic minorities, approximately 87,000 (18%) are living in poverty, and over 38,000 (11%) of those 25 years and older have less than a high school equivalent educational attainment level (US Census 2012). Coastal Georgia's current population that could be exposed to inundation from sea-level rise of 0.9–1.8 m by the year 2100 is estimated to be between approximately 51,000 and 96,000, respectively (Hauer et al., 2016). The exposed population is expected to nearly double when accounting for Georgia's population growth to between approximately 93,000 and 179,000 people by the year 2100 (Hauer et al., 2016). Studies based on 2010 US Census population data estimate that there are approximately 5000 Georgia residents with high social vulnerability living within 0.9 m of the high tide line (Strauss et al., 2014). Taking into account the significant population growth projected for the region, however, it is likely that the socially vulnerable population of the future will be much greater. Moreover, being able to identify and quantify whom those socially vulnerable populations will be is of critical importance for targeting adaptation planning and policies at vulnerable sub-populations.

2.2. Population projections

One of the most well-accepted approaches for projecting populations is the cohort-component method, which uses migration, birth, and death rates to forecast population changes within an area (Smith, Tayman, & Swanson, 2001). Given the difficulty of obtaining these data for some areas and smaller geographies such as US Census tracts, a simpler approach was proposed, known as the Hamilton-Perry method, which uses cohort-change ratios (CCR) between the two most recent census counts to project populations by age and sex, and sometimes race or ethnicity (Hamilton & Perry, 1962; Swanson, Schlottmann, & Schmidt, 2010). Using the Hamilton-Perry method based on 2000–2010 US Census data and a series of controlling factors and limits, we projected populations by age, sex, race, and ethnicity in 10-year cohorts from 2010 to 2050 at both the county (n = 6) and census tract levels (n = 121) for the Georgia coast following:

$$ {}_{n}\mathrm{CCR}_{x} = \frac{{}_{n}P_{x+y,l}}{{}_{n}P_{x,b}}, \tag{1} $$

where n is the cohort interval, x is the starting age of the cohort, ${}_{n}P_{x+y,l}$ is the population aged $x + y$ to $x + y + n$ in the most recent census (l), ${}_{n}P_{x,b}$ is the population aged x to $x + n$ in the second most recent census (b), and y is the number of years between the two censuses ($l - b$) according to Smith et al. (2001).

Given the 10-year interval of most US Census data, the age cohort of 10–19 is the minimum for applying the CCR. Child-woman ratios (CWR) are used to project populations of the 0–9 age cohort. We made two adjustments to Smith et al.'s (2001) recommendation for assessing CWRs. First, we used 10-year age cohorts instead of five-year age cohorts because our projection interval was 10 years. Second, we assessed the combined CWR for the population of male and female children due to low counts for some groups. We calculated CWRs for the launch year's population by calculating the ratio of children aged 0–9 to women aged 15–49 following:

$$ \text{Children aged } 0-9\text{: } {}_{10}P_{0,t} = \frac{{}_{10}P_{0,l}}{{}_{35}P_{15,l}}, \tag{2} $$

We divided this combined CWR by two before calculating the projected target population of male and female children, which assumes an equal birth rate for the sexes. As we projected in 10-year age cohorts over 10-year periods, we used half of the 10–19 aged female population count to ascertain the number of women 15–19 to be included in the 35-year window in equation Eq. (2).

Two challenges emerge when projecting populations for sub-county geographies such as census tracts (Swanson et al., 2010). A common challenge is the frequent changes that occur with boundaries between census collection years. To overcome this first challenge, we applied the Longitudinal Tract Database's conversion tool (Logan, Xu, and Stults 2014) to each 2000 census tract data table to normalize the data to 2010 census tract boundaries. Another common challenge is specific to the Hamilton-Perry method, which can lead to forecast errors and upward bias in rapidly growing areas (Smith et al., 2001). This is due to small populations, particularly those that result in small denominators

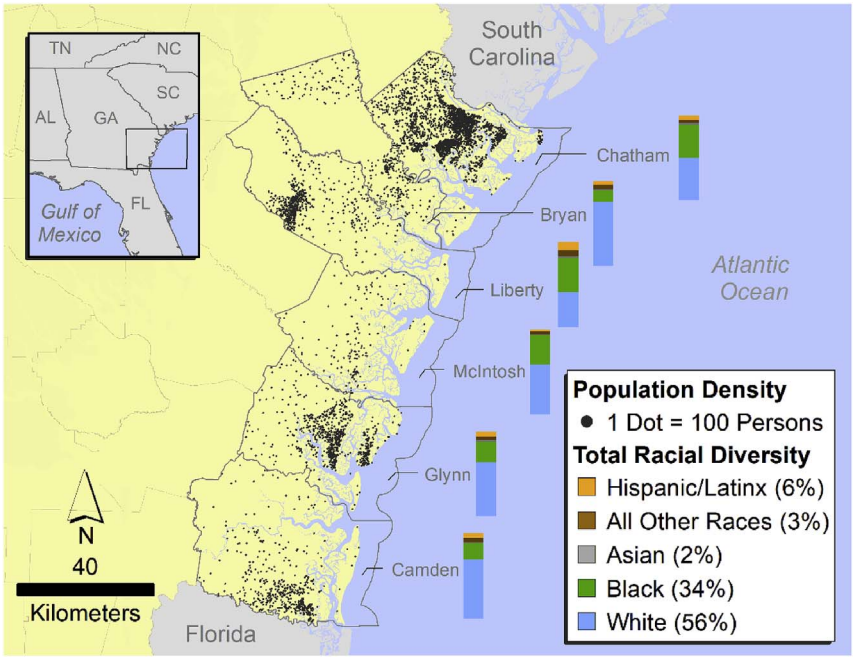

Fig. 1. Study site of coastal Georgia. Racial diversity by county and population density for US Census block groups (US Census, 2012). Stacked bars show the current proportion of racial diversity in each county. Block group outlines are not shown for clarity. Dots are restricted to land only.

in the CCR calculation. For example, a cohort (e.g., Asian women 10–19) with a tract population of 10 for the base year and 100 for the launch year will have a CCR of 10, leading to a population of one million after only four projection periods. This is less of an issue with larger geographies like counties, but can significantly affect results for smaller geographies such as tracts. Consequently, projections must be controlled to independent projections or projections for larger geographies, such as counties, to overcome these errors (Swanson et al., 2010; Baker, Swanson, Tayman, & Tedrow, 2017). The county level projections served as our top-down projections for controlling of the tract level projections.

2.2.1. County level projections

We first projected age-sex cohort populations at the county scale using CCR and CWR as described in Eq. (1) and Eq. (2). We then projected age-sex-race-ethnicity (ASRE) cohort populations at the county scale using CCR and CWR, but also applied a single-dimensional raking to control projections for county ASRE cohorts to our county age-sex cohort projections. This ensures that the sum of demographic sub-populations for the ASRE projections equal the independent age-sex projections within counties. Before applying the single-dimensional raking procedure, we adjusted our uncontrolled projection's CCR for the Hispanic/Latinx population by dividing it by two. This concurs with US Census estimates for a significantly slowed growth rate for this subpopulation over our projection period when compared to the 2000 to 2010 rates (Colby & Ortman, 2015).

2.2.2. Tract level projections

For our initial projections of ASRE cohorts in tract populations, we used the Hamilton-Perry method as above, but we applied four controls to our projections. First, we limited the rate of population change for ASRE cohorts by applying the controlled ASRE county projection's race/ethnicity specific CCR. This was necessary to limit some otherwise rapidly growing or declining cohorts in some tracts with unusually high CCRs (e.g., over 200). Second, to determine the target year's 0–9 age cohort, we did not use CWRs, but instead controlled this group using implied total fertility rates (iTFR) (Hauer, Baker, and Brown 2013) for race/ethnicity specific groups from the controlled county projections, following:

$$ {}_{10}P_0 = 10^* \left[\frac{iTFR *_n W_x}{n} \right], \tag{3} $$

where subscripts are equal to those in Eq. (2) and ${}_nW_x$ equals the total number of women aged x to $x + n$. As with the CWR, we assumed an equal birth rate of both sexes. Third, to limit overly rapid tract population growth or decline we set an annual growth rate ceiling at 1.05 and a floor at 0.98 for *all* tract projections, which is the same as those set in a previous study that applied the Hamilton-Perry method to subcounty geographies (Swanson et al., 2010). This is especially useful in areas that experienced rapid rates of change between 2000 and 2010 that would be unsustainable over a forty-year period due to build out limitations. Lastly, we used a single-raking procedure (Smith et al., 2001) to adjust all tract population projections to county level ASRE counts to ensure tract level projections summed to county level projections.

2.2.3. Low education and poverty projections

To project low educational attainment and poverty, we used 2008–2012 American Community Survey (ACS) US Census data. For low education, ACS Census data are reported as age-sex cohorts of 18–24, 25–34, 45–64, and 65 and above, however, we only assessed low education in populations 25 years and older. Due to our projections being in 10-year cohorts starting with 0–9, we applied a proportional adjustment to our projected population estimate by assuming an equal yearly age distribution among the population for each 10-year age-sex cohort. For example, to calculate the number of women with low education aged 25–34, we divided each of our projected estimates for women aged 20–29 and 30–39 in half and summed the estimated 25–29 and 30–34 counts. To determine the proportion of the future sex-specific population aged 25 and above with low education, we assumed constant enrollment rates and projected the known rates forward. In other words, we assumed that the low education rates for the tract level age-sex cohorts of 25–34 were frozen at the percentages reported in the 2008–2012 ACS data. For example, the female population aged 25–34 in 2010 would be the female population aged 65–74 population in 2050. By assuming constant enrollment rates, we applied the percentage of the population aged 25–34 in 2010 to each new population that entered this specific age-sex cohort during our projections.

For projecting the population of men and women in poverty, we assumed the age-structure of poverty stayed the same over our

projection window. For example, if 10% of the population aged 20–29 was in poverty in 2010, then we applied an in poverty rate of 10% to the population aged 20–29 in all subsequent decades. In other words, we assumed that people moved in and out of poverty as they moved into and out of 10-year age-sex cohorts. This aligns with life course analysis that shows people gain income after age 18 and peak around age 65 before starting to decline again (Tamborini, Kim, and Sakamoto 2015). We acknowledge the uncertainty inherent in ACS data (Spielman, Folch, and Nagle 2014), but contend that our analysis may underestimate poverty rates (Bazuin and Fraser 2013). Our assumption of constant enrollment rates, which assumes "stalled development" is likely an overestimate of the proportion of the future population with low educational attainment (Samir and Lutz 2014), however, projecting multiple scenarios of future educational attainment was beyond the scope of this study.

2.2.4. Population scenarios

The Hamilton-Perry method is a deterministic approach that assumes that the rate of cohort change over two periods (from 2000 to 2010, in our case) stays constant as the population is projected forward into the future. We developed a suite of scenarios, however, that capture the potential for growth or decline in the total population by varying the rate of change for cohorts. We modeled high and low scenarios of ± 5% and intermediate high and low scenarios of ± 1% for our county level age-sex cohort projections, respectively. For example, if the 20–29 female cohort had a 2000 to 2010 CCR of 1.1 (i.e., 10% change over the 10-year period), our high projection scenario would assume a cumulative rate of growth for this cohort of 5% each period. For the 2020 projection under the high scenario, in other words, we would have multiplied the 2010 population by a CCR of 1.15 for this age-sex cohort. We applied the independent, county level projections as controls for our ASRE county and tract level projections following the approach outlined above.

Our scenario approach assumes a homogenous rate of growth or decline for all cohorts. It does not account for the possibility of some sub-populations to grow at faster rates than others grow (other than that rate which is already accounted for in the non-adjusted CCR). The relative rates of growth among sub-populations, for example, is not altered by our scenarios. In other words, all cohorts' change ratios are either increased or decreased equally. Future iterations of our technique could apply alternative scenarios for specific sub-populations. Such scenario building, however, would require more significant input from local planners and/or expert scenario building based on specific sub-populations' rates of migration, births, and deaths, as well as changes in other factors such as economic opportunities, real estate markets, and migration patterns.

2.3. Social vulnerability

There are myriad definitions, frameworks, and models for social vulnerability (Preston, Yuen, and Westaway 2011; see reviews McDowell, Ford, and Jones 2016; Wisner, 2016, pp. 1–52). We take two approaches here, an individual indicator approach and an aggregate-based index approach. For the former, we quantify the number of people in vulnerable sub-populations who are at risk to inundation exposure including racial and ethnic minorities, elderly, women, people in poverty, and people with low educational attainment. We assess absolute and relative change for these sub-populations' risk between 2010 and 2050. For the latter, we use a modified version of the Social Vulnerability Index (SoVI) applied by Emrich and Cutter (2011), but within the conceptual framework of Jurgilevich et al. (2017) where:

$$\text{Risk} = f(\text{Vulnerability, Hazard, Exposure}) \quad (4)$$

In this risk framework, vulnerability is always in the social domain and is driven by the socio-economic conditions that affect a sub-population's potential for harm when physically exposed to an environmental hazard or, in the case of this study, the impacts associated with the gradual environmental change expected from inundation due to future sea-level rise.

We conducted a SoVI-based approach using US Census tracts (n = 121) in the six county region of coastal Georgia for the years 2010 and 2050, but with a few modifications. The SoVI model has undergone a series of updates since its first iteration including 42 variables, then 32, and now the latest version applies 27 variables; these changes have been linked to available data limitations as well as shifts in theoretical understanding of the primary drivers of social vulnerability (Cutter & Morath, 2014). Due to the challenges associated with projecting many of these variables, however, we were limited to only nine of the variables from the latest version in our analysis. Our modeled socio-demographic characteristics that indicate increased levels of social vulnerability include race (specifically Asian, Black, and a non-white/non-Hispanic category we defined as "All Other Races" collected in the 2010 US Census), ethnicity (Hispanic/Latinx), age dependence (≥ 65 or < 5), sex (specifically women), living in poverty, and low education as less than a 12th grade educational attainment level.

The process of implementing SoVI is explained in detail by Dunning and Durden (2011). First, the SoVI model requires that census variables are standardized with z-scores. Second, a Principal Components Analysis (PCA) is conducted on the variables' z-scores using varimax rotation and the Kaiser criterion for component selection (i.e., eigenvalues > 1). Third, the components of the PCA are then interpreted, named, and given a cardinality in relation to their theoretically understood influence on social vulnerability. Fourth, all component scores are summed by the unit of analysis to determine a unit's score. Fifth, scores are then mapped as quantiles to show relative levels of social vulnerability for the study area. The SoVI model assumes a theoretical link of explanatory power exists between the variance in socio-economic indicators and relative social vulnerability of an area. Although this connection is theoretical and difficult to empirically measure across broad geographic regions, we selected the SoVI model for this study due to its popularity in governmental planning (Cutter, Emrich, Morath, & Dunning, 2013; Dunning & Durden, 2011, 2013; see; Evans, Pippin, Hardy, & Hauer, 2014) and because it has been tested for robustness and replicability (Cutter & Morath, 2014; Schmidtlein, Deutsch, Piegorsch, & Cutter, 2008; Tate 2012, 2013).

We ranked social vulnerability of US Census tracts into a three-tiered classification system of limited, moderate, and elevated levels based on standard deviations of SoVI scores following a previous approach (Emrich & Cutter, 2011). We classified social vulnerability of census tracts that scored less than half a standard deviation below the mean score as limited, those within half a standard deviation of the mean as moderate, and those with more than half a standard deviation above the mean score as elevated. We recognize the sensitivity of model results to variable selection (Jones & Andrey, 2007), yet we contend that these variables capture many of the characteristics that are likely to affect Georgia's coastal population under rising seas and maintain that our results are usable in coastal adaptation planning and policies.

2.4. Inundation modeling

To model inundation exposure on dryland, we used continuous elevation data based on high resolution Light Detection and Ranging (LiDAR) point data (10 cm $RMSE_z$ vertical accuracy). We tidally-adjusted the elevation data to the local mean higher high water (MHHW) datum with data available from the National Oceanic and Atmospheric Administration (NOAA OCM, 2015; Strauss, Ziemlinski, Weiss, & Overpeck, 2012). Following a similar approach to Strauss et al. (2014), we employed a conservative three-fold approach to create a land/ocean layer. First, the area had to be above the MHHW mark in the elevation data to be considered land. Second, we marked all areas indicated as marine habitat in the US National Wetlands Inventory as ocean. Third, to ensure hydrologic connectivity between low-lying areas that are

often overlooked in such assessments due to buried culverts not captured in elevation data, we classified streams and canals from the USGS National Hydrography Dataset high-resolution data as “ocean.” To ensure connectivity to the shoreline, we only included areas that are connected to the National Shoreline (NOAA OCM 2016).

2.5. Risk to sea-level rise

By mid-century, Strauss et al. (2014) estimate a range of 0.09–0.55 m of sea-level rise above the 2012 level for the Georgia coast, which is based on locally-adapted scenarios of the Third National Climate Assessment's intermediate low, intermediate high, and high scenarios (Parris et al., 2012). We followed Strauss et al.’s (2014) approach and modeled the same locally-adjusted, mean curves with the intermediate low (globally 0.5 m by 2100) and high (globally 2.0 m by 2100) estimates—what we call slow and fast scenarios for simplicity—to assess sea-level rise inundation for the year 2050. As our moderate scenario, we applied a locally-adjusted estimate for future global mean sea-level rise that is based on a semi-empirical model of sea-level rise (Vermeer & Rahmstorf, 2009) informed by comprehensively modeled greenhouse gas emissions' effect on global warming (Ward and Mahowald 2014) under the Intergovernmental Panel on Climate Change high emissions scenario (see Hardy & Nuse, 2016). To rank relative exposure, we applied the same three-tier classification system as for the SoVI results, but to the percentage area inundated for each tract.

We assessed relative levels of inundation exposure, social vulnerability, and risk (as a function of exposure and vulnerability) for tracts in Georgia's six coastal counties at the year 2050 using the slow, moderate, and fast sea-level rise scenarios. We assumed the populations and sub-populations within each tract were evenly distributed. The proportion of the tract land exposed to inundation was used to determine the proportion of its total population affected. This meant multiplying the projected population density (assessed based on available land) by the area forecast to be inundated under each sea-level rise scenario as done in other studies (Hauer et al., 2016). We only evaluated aggregate social vulnerability (SoVI) for our middle population scenario. We applied this same approach for our individual indicator risk assessment.

A note on terminology for our population assessment. We use “exposed” to indicate the total population that is projected to experience inundation impacts due to sea-level rise independent of vulnerability status. This is the approach of previous studies (Hauer, Evans, and Alexander 2015; Hauer et al., 2016). We use “at risk” to refer to the proportion of population affected in tracts with both elevated social vulnerability and any exposure to inundation from rising seas. We apply “most at risk” to refer to the proportion of the population in tracts with elevated levels of both social vulnerability and inundation exposure following a three-tiered bivariate comparison similar to previously published research (Emrich & Cutter, 2011). For the individual indicator risk assessment, we assess the proportion of each sub-population that is exposed and define these populations as “at risk,” although separately from the previous classifications.

3. Results and discussion

3.1. Future population

Our population scenarios project Georgia's coastal population to range from approximately 439,000 to 1.27 million with a middle projection of 803,000 by the year 2050 (Fig. 2).[1] Under all scenarios, this region becomes a majority non-white population by 2050 with slightly

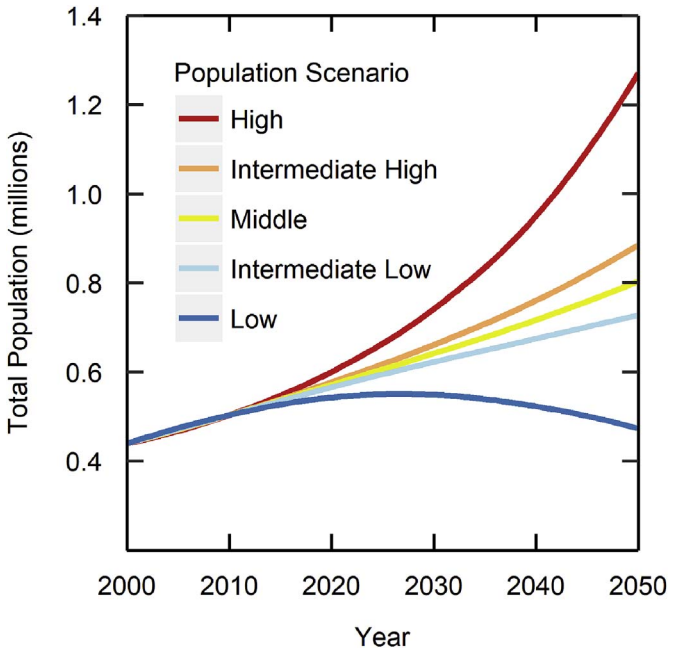

Fig. 2. Population projection scenario totals for coastal Georgia's six counties. Data for 2000 and 2010 are from the US Census (see Section 2.2 for details).

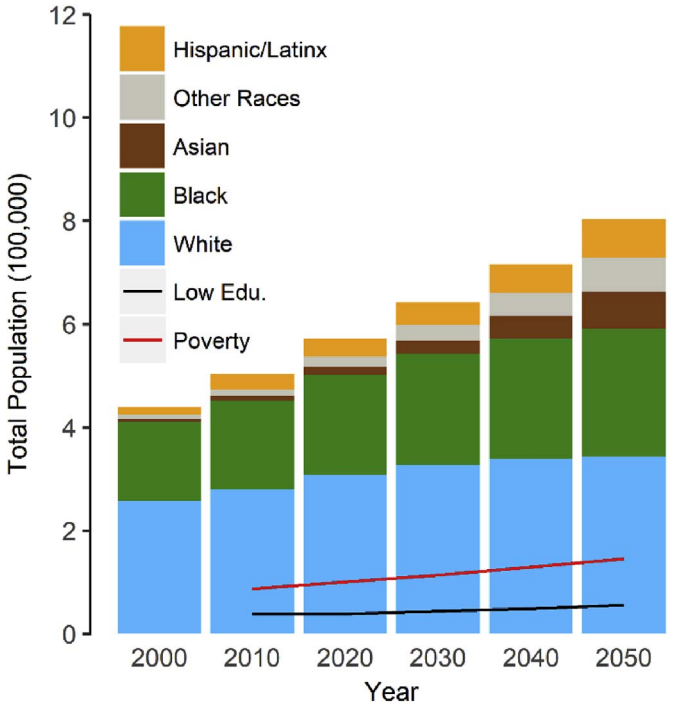

Fig. 3. Sub-population projection (middle scenario) results for coastal Georgia's six counties. Data for 2000 and 2010 are from the US Census (see Section 2.2 for details).

higher rates of poverty and lower rates of low educational attainment (Fig. 3; see Figure S1 for percentages and Figures S2-S5 for results of other population projection scenarios). Compared with the U.S. Census's 2008–2012 American Community Survey estimates, the percentages of coastal Georgia's population aged 25 and above with low educational attainment declines over the projection period from 12.0% in 2010 to 10.3% in 2020 followed by a slow increase to 10.5% by 2050. The total population with low education increases over this time from approximately 38,400 to 55,700 people, a 45% increase (Figure S1 & S6). That the overall percentage of the population with low

[1] Unless stated otherwise, all reported results in Section 3 are for the middle scenario population projection.

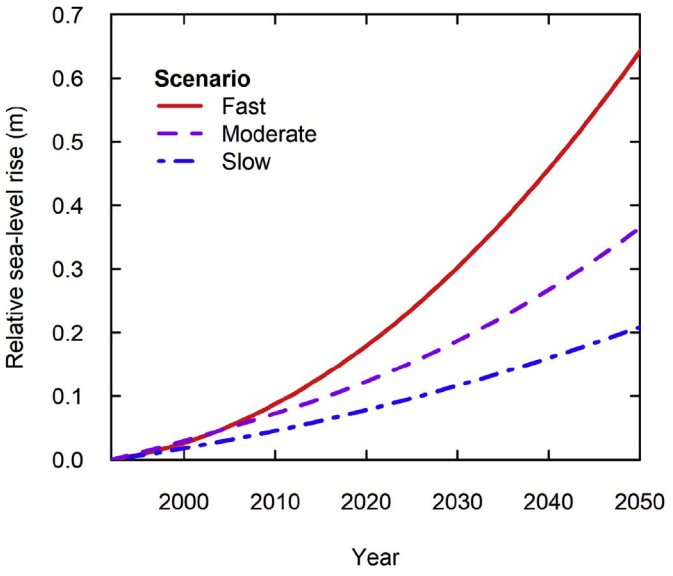

Fig. 4. Locally adjusted mean sea-level rise projection scenarios for coastal Georgia, 1992–2050. See section 2.5 for details of each scenario.

educational attainment decreases suggests this indicator should lead to declines in social vulnerability for coastal Georgia. In contrast, the total population living in poverty is projected to increase from 17.3% to 18.1%, or from approximately 87,000 to 145,000 people; a 67% increase (Figure S1 & S7). This is a relatively small increase in the total poverty rate; however, 0.8% of the projected population equals nearly 6400 more people in poverty than if the rate held constant. Thus, our model projects higher rates of social vulnerability due to an increased rate of those in poverty.

3.2. Future inundation exposure, aggregate social vulnerability, and risk

Our locally adjusted sea-level rise forecasts range from 0.21 to 0.64 m above the local 1992 sea level; the semi-empirically based moderate projection is 0.36 m (Fig. 4). The area of land that would face loss due to inundation by the year 2050 under the three sea-level rise scenarios ranges from 82 to 285 km^2, respectively. This would affect upland areas in 83 tracts for the slow and moderate scenarios and in 84 tracts for the fast scenario. Under the all three sea-level rise scenarios, we project a range of approximately 13,600 to 45,300 people that will be directly exposed to inundation due to sea-level rise by mid-century (Table 1). Of those that are exposed to inundation, approximately 5000 to 14,900 people are projected to be *at risk* (i.e., residing in tracts with elevated levels of social vulnerability). This indicates that approximately 33%–37% of the directly exposed population in 2050 are projected to reside in tracts with relatively high social vulnerability and a limited capacity to cope with the stresses of inundation from sea-level rise. A few tracts (n = 8) are projected to have elevated levels of inundation exposure *and* social vulnerability with approximately 2300 to 10,200 people identified to be the *most at risk* to sea-level rise in the year 2050 (Table 1; also see Fig. 5 for map).

Comparing 2010 and 2050 estimates of population impacted, there is a 67% increase in the total population exposed to sea-level rise under the fast scenario from approximately 27,200 to 45,300 people, which is similar to previous estimates for coastal Georgia (Hauer et al., 2015).

Critically, under the fast sea-level rise scenario our results indicate a much larger total at risk population in 2050 compared to results based on 2010 population data; the most at risk population is projected to substantially increase from about 1500 to 10,200 over this period, a 580% increase (Table 1). We attribute the increase of the at risk and most at risk populations, at least partially, to the relatively higher annual exponential growth rate in tract populations located along the shore with elevated levels of social vulnerability in 2050 (1.60% mean annual growth, n = 21) compared to the growth in all shore adjacent tracts (1.26% mean annual growth, n = 74). In other words, in shoreline tracts there are faster rates of population growth occurring in tracts with relatively higher social vulnerability.

The spatio-temporal changes in the socio-demographic characteristics driving aggregate social vulnerability are revealed by comparing the 2050 and 2010 SoVI results. Using our modified SoVI model, we identified 32 tracts with elevated social vulnerability in 2050 and 33 tracts in 2010 (Figure S8). We observed some overlap in the elevated tracts from 2010 to 2050 (n = 19). The characteristics explaining the elevated tracts stayed relatively consistent with a Class/Race (specifically Black) and Sex component loading as the most important indicators for the study region in both 2010 and 2050 followed by a Race/Ethnicity and Age component (Table 2 and Table S1). Rather than parsing the aggregate index further, we think it is more useful to evaluate the individual indicators of social vulnerability.

Table 1
Population exposed and the aggregate index assessment (via SoVI) for the at risk and most at risk populations. Assessments parsed by county (for 2050 projected population, middle scenario) and each sea-level rise scenario. At risk populations are the proportion of the exposed population in tracts with elevated social vulnerability. Most at risk populations are the proportion of the exposed population in tracts with elevated social vulnerability and elevated exposure.

Sea-Level Rise Scenario	Bryan	Camden	Chatham	Glynn	Liberty	McIntosh	Total by year	
							2050	2010
Slow								
0.21 m in 2050								
Exposed	703	1657	5819	2853	223	2316	**13,571**	**7649**
At risk	0	188	2251	206	21	2316	**4982**	**569**
Most at risk	0	66	0	0	20	2246	**2332**	**25**
Moderate								
0.37 m in 2050								
Exposed	1704	2416	12,435	5484	596	3455	**26,090**	**15,193**
At risk	0	392	4624	756	59	3455	**9286**	**1132**
Most at risk	0	159	0	0	58	3260	**3477**	**71**
Fast								
0.64 m in 2050								
Exposed	2878	3398	23,799	9245	1081	4854	**45,255**	**27,166**
At risk	0	717	7957	1263	126	4854	**14,917**	**2007**
Most at risk	0	283	5626	0	124	4173	**10,206**	**1520**

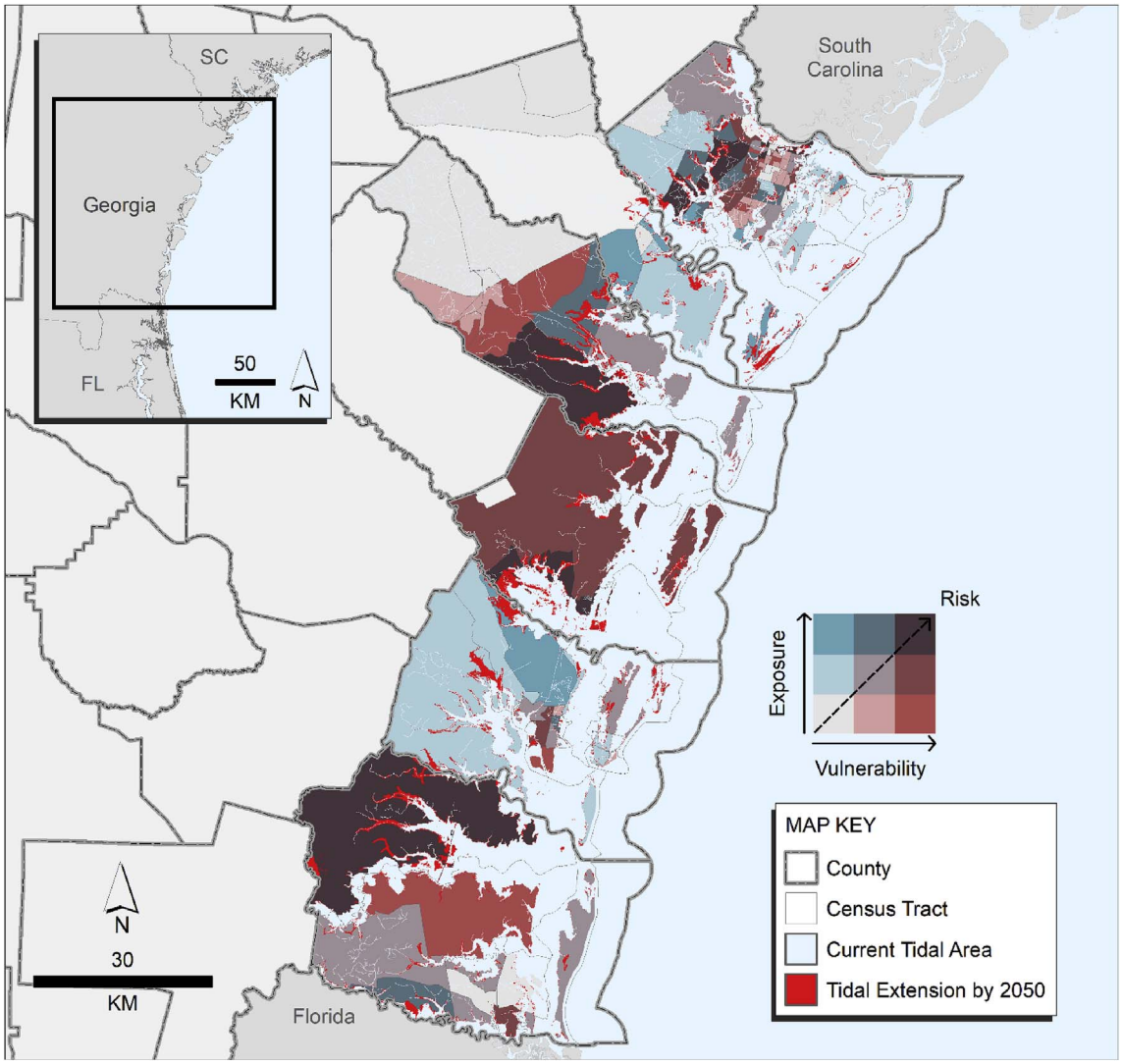

Fig. 5. Coastal Georgia's risk to sea-level rise in the year 2050 under the fast sea-level rise scenario and middle population projection scenario. We used a bivariate plot to map the three-tiered classification schemes for both exposure to sea-level rise inundation (blue shades along y-axis) and social vulnerability (red shades along x-axis). In the plot, relative level of risk increases in the "northeast" direction. The tracts colored dark brown have elevated levels of inundation exposure and social vulnerability.(For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 2
SoVI results including principal components, variance explained, and dominant variable loadings for projected social vulnerability in the year 2050.

Component	Score Adjustment	Component Name	Variance Explained	Dominant Variables	Component Loading
1	+	Class/Race & Sex	38.0%	Poverty	1.096
				Women	0.952
				Black	0.786
2	||	Age & Ethnicity	15.3%	Elderly/ Youth	0.787
				Hispanic/ Latinx	−0.689

3.3. Future projections of social vulnerability indicators

Studies that previously applied SoVI or similar index-based approaches identified relative levels of vulnerability for the region of interest (e.g., Cutter et al., 2003; Emrich & Cutter, 2011; Cutter, 2003; Frazier, Thompson, and Dezzani 2014; Binita, Shepherd, and Gaither 2015). Such assessments problematically assume, however, that the multi-dimensionality and heterogeneity of social vulnerability can be captured in a single aggregate index (Rufat 2013). While composite results are *useful* for broad scale hazard mitigation planning by identifying relative levels of social vulnerability for the study region, their *usability* is limited due to challenges associated with interpretability of the results (Lemos, Kirchhoff, and Ramprasad 2012). Aggregated results are challenging to apply in practice due to obscuring the reason *why* a certain area (e.g., a census tract) is identified as having a higher level of social vulnerability. While policy-makers may prefer an aggregated index, we contend that its usefulness for planning targeted mitigation of socially vulnerable sub-populations is limited (see Rufat 2013 for more discussion on this topic).

To improve interpretation of our aggregated SoVI results, we report the relative importance for each indicator used in our model (Fig. 6). Whereas Table 2 suggests that the variable Black is important for explaining social vulnerability across the region, a map panel of relative importance of individual indicators allows identifying the spatial variability of the most important indicators by census tract. The map panel also shows that the explanation for the elevated levels of aggregate social vulnerability in tracts changes spatially between 2010 (Figure S9 and Table S1) and 2050. The reason that the tract in Liberty County scored highly in the aggregate index model in 2010 (indicated with an asterisk at its center in Figure S8a), for example, was primarily

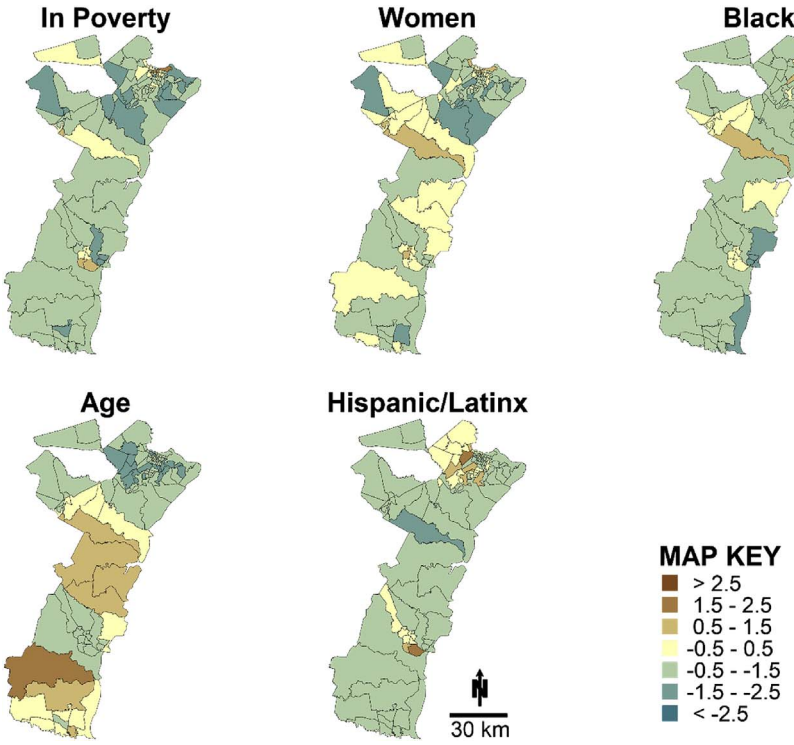

Fig. 6. Year 2050 sub-populations. This map panel shows the relative importance over space for sub-populations typically associated with increased levels of social vulnerability. The map categories are based on standard deviations (SD) from the regional mean for each sub-population projection (middle scenario).

due to a combination of moderately elevated levels of women, people in poverty, and people with low educational attainment (Figure S9). In this tract, by 2050 age dependency becomes a more important factor while poverty becomes less important (Fig. 6). Another example is in the Brunswick urban area, which shows two tracts with high social vulnerability in 2050 (Figure S4b) due to their relatively large Hispanic/Latinx populations and populations in poverty (Fig. 6).

Without showing the map panel, the aggregate social vulnerability results (Figure S8b) would suggest that each tract with elevated social vulnerability across the region would need equally targeted mitigation for all of the characteristics in Table 2, which is not the case (see Fig. 6). We contend that aggregate-based indices are more usable if the underlying spatial variability in indicators driving the regional vulnerability is shown to planners and others working to mitigate uneven social vulnerability at the local scale. The planning actions needed to mitigate vulnerability for an elderly sub-population, for example, will often not be the same set of actions needed for a population in poverty and/or with low education. We now take a step even further away from the aggregate approach and evaluate the at risk populations for each vulnerable sub-population.

Our results show an increase in the absolute number of people at risk for all sub-populations under all sea-level rise scenarios and all but the lowest population projection scenario (Fig. 7; see Figures S10 & S11 for projection estimates of at risk populations due to moderate and slow sea-level rise scenarios, respectively). As the largest sub-population assessed, women are unsurprisingly projected to have the largest increase in exposure. For example, for the middle population projection and fast sea-level rise scenario, women are projected to increase from approximately 14,000 to 24,000 exposed and the Hispanic/Latinx sub-population from approximately 1500 to 4600 between 2010 and 2050. Relatedly, the Hispanic/Latinx sub-population had the largest percent increase from 4.9% to 6.1% between 2010 and 2050 (Fig. 8). Otherwise, our results indicate that most sub-populations will have limited proportional increases (i.e., ~0.5% or less) in their risk to inundation from sea-level rise under the fast scenario (see Figures S12 & S13 for the moderate and slow sea-level rise scenarios).

Our findings suggest that while coastal Georgia will experience an

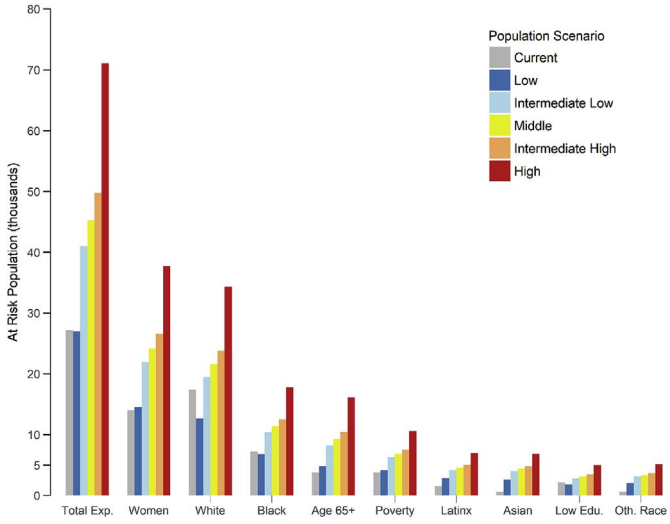

Fig. 7. Absolute change in total and vulnerable sub-populations (including white sub-population) to inundation exposure under the fast sea-level rise scenario by 2050.

absolute increase in the exposure of the total population and the risk for all vulnerable sub-populations under all sea-level rise scenarios, the region will see limited change in the relative proportion of each sub-population at risk (except for the rapidly growing Hispanic/Latinx sub-population). One of the main messages from this key finding is relevant for interpreting previous and future studies quantifying social vulnerability of populations in coastal regions when using current population counts. For those coastal areas experiencing rapid growth (or declines) in more socially vulnerable sub-populations, estimates are likely to underestimate (or overestimate) the proportion of that group that will be impacted by inundation due to future sea-level rise. Based on the large historical growth for coastal populations in the United States (Crossett et al., 2013), and the estimated future population growth expected near the shoreline (Hauer et al., 2016), we believe that future studies that estimate socially vulnerable populations in relation to sea-

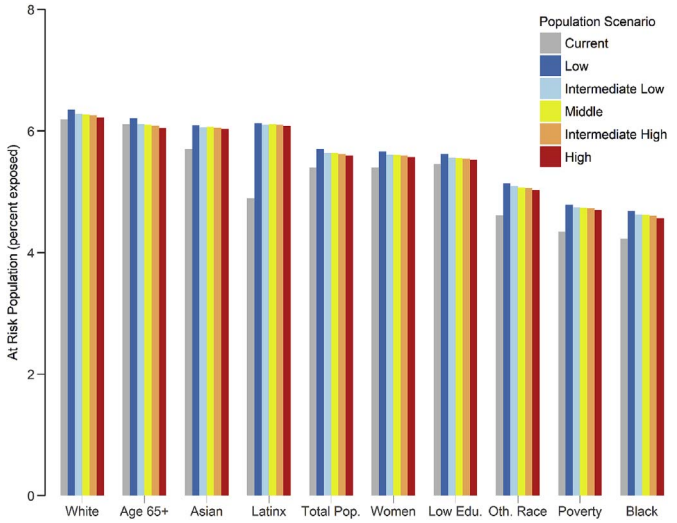

Fig. 8. Percent change in total and vulnerable sub-populations at risk (including white sub-population) to inundation exposure under the fast sea-level rise scenario by 2050.

level rise should account for this phenomenon to improve their accuracy and relevance for long-term adaptation planning.

3.4. Comparisons and limitations

Based on our middle population projection scenario, our findings indicate that coastal Georgia's future population at risk to sea-level rise of 0.64 m by 2050 of 14,900 people is projected to be nearly triple one previous estimate of 5000 based on 2010 population data (Strauss et al., 2014). We acknowledge that our inundation model did not explicitly take into account human-made barriers such as levees that the previous study included (Strauss et al., 2014). We believe, however, that inclusion of levees and seawalls would make a fractional improvement over the LiDAR-based elevation data. Further, we contend that these future populations would still be living below mean sea level, and as a result would be more at risk to the effects of sea-level rise including storm surge that may override the engineering solutions already in place (e.g., as with Hurricane Katrina; Leavitt & Kiefer, 2006), or even innovative solutions of the future. Moreover, ours is a more conservative estimate, assessing the population below 0.64 m compared with the previous study's use of 0.9 m. This explains why our 2010 estimate of 2010 is lower than the previous study's estimate, at least partially.

Our findings match reasonably well with other studies for this region. For example, using a different methodology Hauer et al. (2015) reported similar magnitudes for the total population projected to be exposed to inundation due to sea-level rise by mid-century. Their projected mean estimates ranged from around 7300 to 41,400 people compared to our middle scenario estimates of 13,600 to 45,300 (Table 1). The differences are likely related to our study using a different population projection method as well as different curves for sea-level rise. We applied locally-adjusted upper and lower bounds following the quadratic equation reported in Parris et al. (2012), which forecasts lower rates of rise by 2050 than the curves used by Hauer et al. (2015; see Clough, Park, and Fuller 2010). Hauer et al.'s (2015) higher curve would suggest that their estimate should be higher than our estimate. We used a different population projection methodology than Hauer et al. (2015)—the Hamilton-Perry method—which is known to have an upward bias for areas undergoing rapid population growth (Swanson et al., 2010). That our estimates for the total population exposed are within a reasonably close range of Hauer et al.'s (2015) suggests that our approach aligns well with at least one independent projection for this region.

There are a few limitations to our approach worth acknowledging. First, we did not apply tract-specific limitations on growth, which would take into consideration "build-out" scenarios. We believe that our upper limits on global tract level growth controlled for this reasonably well. Under our highest population projection scenario, for example, the most densely populated tract (located in the city of Savannah) increased from approximately 3000 to 8000 people per square kilometer between 2010 and 2050. This is well within the feasible population density for an urban tract (Holt, Lo, and Hodler 2004). Second, we did not account for the possibility of technological innovations in coastal adaptation—including coastal emigration—that could lower the exposure of future populations, as this was beyond the scope of this project (more below). Racial and ethnic change are captured in our cohort change ratio, yet we held the structure of poverty constant (based on 2010) across time while the population changed and used constant enrollment rates for low education, which assumes stalled growth in educational attainment. Third, our model assumes that each specific sub-population's 2000 to 2010 CCR will stay steady over a 40-year window.

A fourth limitation is that our approach does not incorporate the effect of amenity migration or gentrification on a population's socioeconomic structure (Hwang and Sampson 2014). CCRs implicitly account for both migration and mortality dynamics within a single age group's CCR. There still remains the possibility that sea-level rise will dramatically alter future migration patterns (Hauer 2017); however, our projections do not account for possible changes in migration patterns. We consider our use of various CCR scenarios as implicitly capturing these potential changes in total population migration patterns. It should be noted that migration data is rarely published at sub-county scales, potentially hampering future empirical migration scenarios at these scales. The use of CCRs for sub-county population projections are within acceptable projection approaches (see Baker et al., 2017). We do not account for all possible mechanisms that would lead to changes in specific group's CCRs (like economic opportunity, real estate market impacts, gentrification, etc.), but we do account for upper and lower bounds in our projection approach. Future studies that took more specific scenario building into consideration could more explicitly account for these dynamics and would be an improvement upon our approach.

Finally, we did not model a "full" spectrum of vulnerability indicators, as is typically done with the SoVI model using observed census data (Cutter & Morath, 2014). We recognize that this limits our aggregate model's ability to capture the multi-dimensional nature of vulnerability as well as how different indicators have interactive effects that further exacerbate a group's vulnerability. For example, being an elderly white woman with low educational attainment would likely result in a greater vulnerability to sea-level rise than being elderly, but with a college degree and significant income or savings. Whereas the latter would have the capacity to move in the face of rising seas, the former would be limited in their ability to generate the resources needed to relocate. Moreover, we do not account for factors such as female head of household, as this would likely parse our data to the degree that nearly all of our CCRs would run towards zero and lead explosive growth rates by creating small denominators. We can imagine future work that takes our approach of temporally matching future populations with future environments and adds future economies to the creation of scenarios, much like the Shared Socioeconomic Pathways approaches recently developed for the Intergovernmental Panel on Climate Change (e.g., Samir and Lutz 2017; Lutz and Muttarak 2017). How such scenarios are downscaled to sub-county geographies, however, remains a challenge for projecting the social vulnerability of future populations.

4. Conclusion

We applied a theory of socio-demographic change, demographic metabolism (Lutz, 2013), to project social vulnerability and improve a

sea-level rise risk assessment of coastal Georgia. We projected coastal Georgia's population to become majority non-white with higher rates of poverty and lower rates of low educational attainment by the year 2050. Our findings show that estimating the impacts on current socially vulnerable populations, as either aggregate indices or vulnerable sub-populations, leads to underestimating the absolute magnitude (and in many cases the proportion) of socially vulnerable populations of the future that will experience inundation from future sea-level rise under all the but the lowest population scenario. Importantly, our findings demonstrate how studies that assess social vulnerability based on current population counts are likely underestimating not only the absolute magnitude of sub-populations at risk, but also the proportional risk of sub-populations experiencing rapid growth in coastal regions.

Our temporal alignment of the social vulnerability of future populations with inundation exposure contributes knowledge toward "use-inspired research on vulnerability and adaptation" (Moser 2010, p. 467) with the goal of generating policy solutions for mitigating vulnerability to rising seas. We believe that our approach can empower local and state governments to develop more appropriately oriented vulnerability mitigation plans, targeting those with low educational attainment in specific areas, for example, while specifying needs for those in poverty in others. We imagine that our methodological approach of projecting future socially vulnerable populations and their relative risk could improve upon previous investigations (e.g., see Frazier et al., 2010 for storm surge; see Grineski et al., 2012 for heat-waves) in future climate-related hazard and climate justice studies.

Despite the limitations, we believe the approach we have presented answers a pressing need for more climate models that integrate climate change scenarios with scenarios of future social heterogeneity by accounting for poverty and other factors driving social inequality (Rao, van Ruijven, Bosetti, & Riahi, 2017). Moreover, we believe that our approach for doing such integration at the sub-county scale—a more manageable scale for the city and county planners who will be coping with these changes—is an innovation on the national and global scale integrated assessments that are the current focus of integrated modeling.

Declaration of interest

The authors have no conflict of interest.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.apgeog.2017.12.019.

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